Risk and Structural Instability in US House Prices

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Abstract

This paper employs a Component GARCH in Mean model to show that house prices across a number of major US cities between 1987 and 2009 have displayed asset market properties in terms of both risk-return relationships and asymmetric adjustment to shocks. In addition, tests for structural breaks in the mean and variance indicate structural instability across the data range. Multiple breaks are identified across all cities, particularly for the early 1990s and during the post-2007 financial crisis as housing has become an increasingly risky asset. Estimating the models over the individual sub-samples suggests that over the last twenty years the financial sector has increasingly failed to account for the levels of risk associated with real estate markets. This result has possible implications for the way in which financial institutions should be regulated in the future.

Keywords House prices · Risk · Structural instability · CGARCH

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Introduction

This study of the US housing market investigates whether house prices share similar properties to other assets, such as equities and commodities, in terms of a significant risk-return relationship and asymmetric adjustment to shocks, as identified in studies reviewed in Engle (2004). A second contribution of this study is to determine the extent of any structural instability over the last twenty years in house price volatility, by testing for structural breaks in the mean and variance. Accounting for structural instability also facilitates the estimation of models using structurally stable sub-samples, which ensure that the estimates are valid.

As concluded by Case et al. (2005) the US housing market has an important effect on the US economy and financial markets generally, with the related issue of housing market volatility and risk becoming one of increasing prominence following problems in the sub-prime mortgage market. In this paper we employ an asymmetric version of the Component Generalised Autoregressive Conditionally Heteroskedastistic-in-mean (CGARCH–M) model to test for these properties using monthly US city-based house price data.

Although there are several US house price studies, such as Case and Shiller (1989), Bond et al. (2003) and Cappoza et al. (2004) among others, Miller and Peng (2006) note that there have been very few attempts to explicitly model house price volatility; however Dolde and Tirtiroglue (1997) use the standard GARCH model to show evidence of a link between house price volatility and the regional economy in the USA. Miller and Peng (2006) themselves use GARCH models, with a panel VAR, to analyze interactions between volatility and general economic indicators. In addition Miles (2008) uses the GARCH technique to model uncertainty in housing investment, showing that uncertainty has a negative effect. There are, as far as we are aware, fewer studies concentrating on volatility and specific tests for structural breaks in the variance of house prices, although Hall et al. (1997) use a switching error correction model to show that instability and rapid house price increases in the UK are associated with unstable regimes or samples. Guirguis et al. (2005) note the structural instability in US house prices, which they model using a time-varying coefficient approach as well as the rolling GARCH models, while Chien (2010) presents empirical evidence for the impact of real estate policies and financial crises in terms of structural breaks in regional house prices in Taiwan.

The main potential breaks in our dataset are associated with various financial crises in the US during the estimation period; in particular the secondary banking crisis of the late 1980s and early 1990s, and more recently during the post-2007 period characterised by a collapse in mortgage lending and house prices. In keeping with much of the literature on asset markets (e.g. Granger and Hyung, 2004), we determine the breaks endogenously rather than specifying a particular policy determined break. [1] Adopting this approach allows the break dates to incorporate information on the inevitable leads/lags that are likely to be present. Given the limitation of the standard

[1] When employing this approach, often used with asset market based studies (Timmermann, 2001; Granger and Hyung, 2004), specific explanations for identified breaks are rarely provided. This is due to the nature of asset markets, where the market will often react to changes in policy or the economy long before they are implemented or even announced. This makes it difficult to attribute breaks to specific events. In addition, breaks in asset markets can typically occur due to bubbles or swings in investor perceptions, Hall et al. (1997) use this as a general explanation for shifts in regime in their study of housing markets. The alternative approach would involve specifying a particular break based on specific policy changes as originally used by Enders (1988). It is important in this literature, as elsewhere, to avoid spurious interpretation of breaks, which are likely to be the result of complex interactions of effects and not susceptible to simple analysis.

structural break tests, such as the Chow test, which are restricted to breaks in the mean, this study employs a variety of techniques to endogenously determine breaks in both mean and variance, such as in Kim and Nelson (1999).

Following the introduction, the paper provides a brief description of the methodology employed in the study, relating to the asymmetric CGARCH-M model and methods used to determine the breaks. The data and results are then discussed, prior to providing some conclusions and suggested policy implications.

Methodology

As based on the original ARCH model (see Engle, 2004), the CGARCH-M model has proven to be popular for investigating asset behaviour since its introduction by Engle and Lee (1999). It also possesses some useful econometric advantages over other GARCH class models[2], such as not requiring the assumption of mean reversion in volatility. This feature is particularly useful in modelling US house prices, as recent problems suggest that the risk and return profile of real estate lending in the US could have a long-run time-varying component, as noted by Guirguis et al. (2005). The identification of any risk-return relationship requires the incorporation of the conditional standard deviation, which reflects the risk, in the mean equation of the model, with the test for any asymmetry accounted for by the following asymmetric CGARCH-M model specification:

[2] As an alternative the more commonly used Threshold GARCH-M (Glosten et al., 1993) model was also employed to test for positive risk-return trade-off and asymmetry, with broadly similar results. We could also have used a multivariate form of GARCH, but the substantial differences in how the models perform in different cities with respect to the structural breaks and CGARCH specification made this impossible.

$$\Delta \ln hp_t = \mu + \delta\sigma_t + \varepsilon_t \quad N(0, \sigma_t^2) \tag{1}$$

$$\sigma_t^2 - q_t = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})d_{t-1} \tag{2}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{3}$$

where $d_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, $d_{t-1} = 0$ otherwise, and the parameters are expected to take the following form:

$\delta > 0$ if agents are risk averse,

$(\alpha + \beta) < 1$ as a requirement for stationarity,

$\rho < 1$ again for the stationarity assumption,

$\gamma > 0$ if there is evidence of transitory leverage effects,

$\rho > (\alpha + \beta)$ if as expected the long-run volatility component is more persistent than the short-run,

ϕ is the forecast error.

In the present context $\Delta\ln hp_t$ is the first-difference of the logarithm of the individual city house price, which is in effect the return on owning a house and σ_t is the conditional standard deviation.[3] If $\delta > 0$ we conclude that investors are risk averse, which implies that for the same level of return, investors would prefer a housing asset which is less risky. Similarly, investors are risk neutral if $\delta = 0$ and risk lovers if $\delta < 0$. This is an important conclusion because if investors are risk averse, they are more likely to quantify and monitor the riskiness of their real estate assets and most importantly conduct effective risk management. If they are risk neutral or risk lovers, whereby risk is viewed not to be an important factor when considering a real estate

[3] This is a standard mean equation in nominal form, as in comparable tests on other assets, as used by Glosten et al. (1993), although other studies have incorporated ARIMA type models and the interest rate in the mean. However, this is beyond the scope of this study.

investment, then they are less likely to conduct any form of risk management or even risk assessment.

Also σ_t^2 is the conditional variance, and q_t is the long-run time-varying volatility component as described in equation (3), whilst equation (2) describes the transitory component, which converges to zero with the power $(\alpha+\beta)$. q_t converges on ω with powers of ρ, where ρ typically has a value just below unity indicating very slow adjustment. Additionally, d is a dummy variable reflecting a negative shock (when the error term is negative as in Glosten et al., 1993) and it is assumed that $\gamma > 0$ if a transitory leverage effect applies such that bad news increases volatility, and is similar to the methodology of Glosten et al. (1993). The leverage effect in this case relates to falling house prices causing the debt to housing equity ratio of home owners to rise, increasing the risk associated with home owning.

The remainder of this section describes the statistical procedures that we employ in order to identify the regimes of each series. This procedure involves two steps; first, 'nominating' dates for breakdates and second 'awarding' the breakdate property to certain nominations.

The 'Nominating Breakdates' Stage

The first step is termed the '*Nominating Breakdates'* stage and concerns the identification of specific dates as potential (nominated) breakdates. A variety of statistical tests have been developed for this purpose recently, several of which are used in this investigation.[4] The following tests are included in the study:

(i) IT (Inclan and Tiao, 1994)

[4] Note that although it is not done in this paper, it is relatively trivial to condition on observables – in the simplest case by nominating the 'official' or 'widely accepted' breakdates of each series.

(ii) SAC_1 (The first test of Sansó et al., 2003)

(iii) SAC_2^B, SAC_2^{QS}, SAC_2^{VH} (The second test of Sansó et al. (2003), with the Bartlett kernel, the Quadratic Spectral kernel, and the Vector Autoregressive HAC or VARHAC kernel discussed by Den Haan and Levin (1998) respectively.)

(iv) KL^B, KL^{QS}, KL^{VH} (The refined Andreou and Ghysels (2002) version of the Kokoszka and Leipus (1999) test with the Bartlett kernel, the Quadratic Spectral kernel, and the VARHAC kernel correspondingly.)

There are a number of justifications for choosing these tests as, although all of these tests are designed to detect a structural change in the volatility dynamics, Karoglou (2006b) has shown that many cumulative sum (CUSUM) type tests (including all the above) do not discriminate between shifts in the mean and shifts in the variance.[5] This is an important feature as all types of breaks need to be considered for this study. In addition with these CUSUM-type tests the properties for strongly dependent series have been extensively investigated (e.g. Andreou and Ghysels, 2002; Karoglou, 2010) and there is evidence that they perform satisfactorily under the most common ARCH-type processes. Even when there is a break found in a conditionally heteroskedastic process these tests are able to detect it, as these tests do not exhibit size distortions and also have considerable power, regardless of whether the assumption of within-segment homoskedasticity is applied in order to include the ARCH-type structures. The relative performance of each of the above tests depends on the underlying data generating process (DGP)[6], but since the true DGP is not known it is preferable to use them all and then select the breakdate according to an appropriate set of rules.[7]

[5] This work generalised the results of Bos and Hoontrakul (2002) who refer to the IT test. For further discussion on the difference of all the tests used in this study see Karoglou (2006a).

[6] For example, the IT is found to be the most sensitive to the existence of volatility breaks for independent and identically distributed data, but suffers severe size distortions for strongly dependent

The above set of tests can also be used to identify multiple breaks in a series, which can be achieved by incorporating the breaks in an iterative scheme (algorithm) and applying the breaks to sub-samples of the series. In this study, the algorithm used is comprised of the following six stages:

(i) Calculate the test statistic under consideration using the available data.

(ii) If the statistic is above the critical value, split the particular sample into two parts at the corresponding point.

(iii) Repeat steps 1 and 2 for the first segment until no more (earlier) change-points are found.

(iv) Mark this point as an estimated change-point of the whole series.

(v) Remove the observations that precede this point (i.e. those that constitute the first segment).

(vi) Consider the remaining observations as the new sample and repeat steps 1 to 5 until no more change-points are found.

The above algorithm is implemented with each of the (single breakdate CUSUM-type) test statistics described above (i.e. IT, SAC_1, SAC_2^B, SAC_2^{QS}, SAC_2^{VH}, KL^B, KL^{QS}, KL^{VH}) and is applied to each series in ascending and descending time order so as to avoid potential masking effects. Then the nominated breakdates for each series are simply all those which have been detected in both cases.

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data or for non-mesokurtic distributions. In contrast, the KL and the SAC_2 variants do not exhibit size distortions in these cases but their power is smaller, while SAC_1 does not exhibit size distortions for non-mesokurtic data and although it does for strongly dependent data, its power is higher than KL and SAC_2.

[7] For example, a selection rule could suggest that a breakpoint can be considered only if two tests have identified it; or a breakpoint can be considered only if the resulting segments contain more than 10 observations.

The 'Awarding Breakdates' Stage

The second step involves the procedure adopted to choose which of the nominated breakdates are in fact the actual ones. In this study, the procedure in essence is about uniting contiguous nominated segments (i.e. segments that are defined by the nominated breakdates) unless one of the following conditions is satisfied:

(i) the means of the contiguous segments are statistically different (as suggested by the t-test)

(ii) the variances of the contiguous segments are statistically different (as suggested by the battery of tests, which is described below)

(iii) the Kolmogorov-Smirnov test suggests that the distribution of each segment is different

This testing procedure is repeated until no more segments can be united, or in other words until no condition of the three above is satisfied for any pair of contiguous segments.

In general, if the power of the Kolmogorov-Smirnov test was satisfactory, then (iii) would suffice. Since this is not the case, conditions (i) and (ii) are necessary in order to ensure that most, if not all, breaks are indeed taken into account. With regards to the battery of tests mentioned in condition (ii), it involves several statistical tests designed to test for the homogeneity of variances of different samples and in this case these samples are two contiguous segments. These tests constitute a different approach to the CUSUM-type tests described previously in that they test for the homogeneity of variances of distinct samples, that is, without encompassing the time-series dimension of the data.[8] They include the standard F-test, the Siegel-Tukey test

[8] Therefore, they provide the same value even if the observations of each segment are randomly ordered. In contrast, statistics that are based on sequential methods (such as the CUSUM tests) are influenced by the order of the observations.

with continuity correction (Siegel and Tukey, 1960, and Sheskin, 2011), the adjusted Bartlett test (see Sokal and Rohlf, 1995), the Levene test (1960) and the Brown-Forsythe (1974) test.

Overall, the F-test requires equal sample sizes and is sensitive to departures from normality.[9] On the other hand, the Siegel-Tukey test is based on the assumption that the samples are independent and have the same median. The Bartlett test is also robust when the sample sizes are not equal despite it still being sensitive to departures from normality. Its adjusted version makes use of a correction factor for the critical values and the arcsine-square root transformation of the data to conform to the normality assumption. The Levene test (1960) is an alternative to the Bartlett test albeit less sensitive to departures from normality. Finally, the Brown-Forsythe (1974) test is a modified Levene test (substituting the group mean by the group median) and appears to be superior in terms of robustness (when scores are highly skewed or samples are relatively small) and power.

Data and Results

In order to utilise the high frequency required to better measure volatility, the study employs monthly city-based house price data for the USA running from January 1987 (the earliest available) to January 2009.[10] The data is taken from Standard and Poor's version of the Case-Shiller house price index, which uses repeat sales regression

[9] See Karoglou (2010) for a discussion of non-normality and the presence of structural breaks as well as a more detailed discussion of some of the implications of this type of approach to finding breaks in the variance of a series.

[10] A composite house price index covering the main US cities was also estimated, however there was no evidence of a significant risk-return trade-off or asymmetric adjustment (the results are available from the authors on request). This result reflects the varying nature of risk and the housing market across the US, and that in a composite form the effects tend to cancel each other out. This supports a

techniques (Case and Shiller, 1989). The five US cities selected for testing - New York, Los Angeles, Chicago, Portland and Miami – provide a geographical spread. The first three have populations over 1 million whilst Miami and Portland are included as the main cities, for which there is data, in the southern and north-western part of the country respectively. To produce a return measure, the data is logged and differenced in the standard way. All estimations of the CGARCH-M models were carried out using the Bollerslev-Wooldridge robust standard errors and covariances, with conditionally normal errors. Table 1 contains the summary statistics and shows that Los Angeles and Miami have the most volatile house prices and Portland has enjoyed the highest growth rates over the last twenty years. The Jarque-Bera statistics for most of the house price indexes are highly significant, reinforcing the use of the Bollerslev-Wooldridge robust standard errors and covariances.

Table 2 provides a summary of the structural breaks in the series, with Table 3 identifying breakdates for each city by test. The latter suggests that overall, in most cases, the nominated breakdates introduce a change both to the mean and variance of the series with only five notable exceptions. On the one hand, the first break in the Chigago series (1990m03), the second break in the Miami series (2004m02), and the fourth break in the New York series (2008m05) appear to relate to a change only in the variance, although in the last case this could be attributed to the small number of observations of the contiguous segments. On the other hand, the third break in the Chicago series (2008m11) and, to a certain degree, the third break in the Portland series (2008m01) both seem to be associated with a change only in the mean

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similar result to Case and Shiller (1989), who found little evidence of any relationship between individual city prices and a composite index

Application of the structural break methodology identifies a break in the data for all the cities in the early 1990s, except Miami, indicating that the US housing market and economy changed with regard to the way housing risk was perceived. (See tables 2, 3 and 6). The second wave of breaks occurs in the early 2000s, with only Miami producing a break prior to 2001. Finally all five cities experienced a series of breaks in 2007 and 2008 as the risk profile of housing investments changed rapidly as the financial crisis worsened. The models are only estimated for the sub-samples where there is at least three years data to allow enough observations to provide a reasonable level of degrees of freedom. During the final two years where multiple breaks are identified there are insufficient observations to allow estimation of the sub-sample.

The results of the asymmetric CGARCH-M model are presented in Table 4, with the results from the sub-samples reported in Table 5. They suggest that for the US cities tested here, there is strong evidence of a significant risk premium in housing assets, with a positive risk/return trade-off, indicating a higher return is required to compensate for higher risk, with the exception of Chicago and Los Angeles. These results complement those in other studies, such as Dolde and Tirtiroglou (1997) who also find a negative and significant risk premium for some cities.

With regard to the conditional variance equation, there appears to be mixed evidence of asymmetric adjustment, with only Chicago and Los Angeles providing significant evidence of the leverage effect, whilst in Portland there is evidence that negative shocks produce lower volatility. In most of the cities the value of ρ, measuring the speed of convergence to the long-run level of volatility, is significant, positive and less then unity. However Chicago has a value of unity indicating potential instability, whilst the others have values of approximately 0.98 indicating very slow adjustment. In addition, as $(\alpha + \beta) < 1$ all models are stationary.

In the sub-samples, the results are very different to the entire sample, which emphasises the need to account for the structural breaks in the data. The main difference relates to the risk premium, which in general is significantly positive or insignificant until the break in the early 1990s, suggesting investors are mainly risk averse when making their investment decisions. With the exception of Chicago, the other four cities all have a negative and significant risk premium after the break in the early 2000s, which suggests investors had become less concerned with risk.

In addition to changes in the risk-return relationship, substantial differences are noted in terms of asymmetry and adjustment to q_t. The sub-sample results in general include more insignificant variables, suggesting the dynamics are much simpler when the structural breaks are accounted for. This is in accordance with the theory, as breaks induce higher mean and/or volatility persistence. As a result there is little evidence of asymmetric adjustment over the sub-samples, although there is some in more recent periods. In addition, the speed of adjustment is generally quicker in more recent samples, possibly reflecting the increased use of market-based means of funding for the US housing market.

Concluding Remarks

Although there is evidence of a significant relationship between risk and return in US house prices, the relationship has varied over the different sub-samples. While there appears to be a positive relationship during the late 1980s, it changes to a negative relationship after 2001, as investors fail to appropriately account for the levels of risk in the housing market. Although there is some evidence of asymmetric adjustment over the whole sample, this disappears when the models are estimated in sub-samples; again emphasising the importance of taking into account the structural breaks. The structural break tests indicate multiple breaks across all cities, particularly in the early

1990s and post-2007, during which period the housing market has experienced wild changes in its perceived risk.

In general, using CGARCH-M models, in addition to splitting the models into separate sub-samples, has produced a result that reflects the time varying nature of risk in the market over recent years as the riskier sub-prime sector has expanded. The policy implications of our results, suggesting a need to view housing more like other assets, is particularly relevant for mortgage lenders who, in recent years, have increasingly treated housing as an investment which possibly does not have the level of risk suitably priced.

There is a further implication that, as with other assets, there is the potential for further house price adjustment back to long-run levels, which in turn has important implications for lenders as well as homeowners. Apart from the appreciation that house price volatility can have detrimental effects on the economy, including negative equity and mortgage foreclosure losses, the safety and integrity of housing investment and associated mortgage lending is an area of generally growing concern given the worldwide repercussions of sub-prime market problems. The importance of housing finance risk also has important implications for the way in which the banking sector is supervised and for its lending practices to the property sector.

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Table 1 Summary Statistics for the Difference in Logged Case-Shiller House Price Indices

City	Chicago	Los Angeles	Miami	New York	Portland
Mean	0.003	0.004	0.003	0.003	0.005
Max	0.024	0.033	0.028	0.018	0.025

Min	-0.044	-0.039	-0.044	-0.017	-0.022
St. Dev.	0.007	0.012	0.011	0.007	0.007
JB	1253.771	23.353	206.241	2.895	82.136

265 monthly observations. JB is the Jarque-Bera statistic (chi-squared (2))

Table 2 Summary of Structural Breaks for the Difference in Logged Case-Shiller House Price Indices.

City	Chicago	Los Angeles	Miami	New York	Portland
Segment 1	Start - 1990m2	Start – 1993 m12	Start – 2000m10	Start – 1991m4	Start – 1991m3
Segment 2	1990m3 – 2007m3	1994m1- 2003m6	2000m11– 2004 m1	1991m5 – 2002m3	1991m5- 2005m2
Segment 3	2007m4 – 2008m10	2003m7 – 2007m9	2004m2 – 2007 m8	2002m4 – 2007m4	2005m3 – 2007m12
Segment 4	2008m11 - end	2007m10- end	2007m9 - end	2007m5 – 2008m4	2008m1 - end
Segment 5				2008m5 - end	

Table 3 Breakdates for the Difference in Logged Case-Shiller House Price Indices

City	IT	SAC_1	SAC_2^B	SAC_2^{QS}	KL^B	KL^{QS}
CH	1990m03	1990m03		1990m03		1990m03
	2007m04	2007m04		2007m04		2007m04
	2008m11					
LA	1994m01	1994m01		1994m01		1994m01
	2003m07	2003m07		2003m07		2003m07
	2007m10	2007m10		2007m10		2007m10
MI	2000m11	2004m02	2004m02	2004m02	2004m02	2004m02
	2007m05	2007m09		2007m09		2007m09
NY	1991m05	1991m05		1991m05		1991m05
	2002m04	2002m04		2002m04		2002m04
	2007m05	2007m05		2007m05		2007m05
	2008m05	2008m05		2008m05		2008m05
PO	1991m04	1991m04		1991m04		1991m04
	2005m03	2005m03		2005m03		2005m03

All statistics are significant at the 1% level of significance except those that are shaded which are significant at the 5% level The above refer to dates with year followed by month. See text for a description of the above tests. 'B' refers to the use of the Bartlett kernel with the Newey-West automatic bandwidth selection procedure, and 'QS' to the quadratic spectral kernel.

Table 4 CGARCH –M results using the Difference in Logged Case-Shiller House Price Indices (full sample)

City	Chicago	Los Angeles	Miami	New York	Portland
μ	0.008*	0.009*	0.002*	0.000	0.005*
	(27.505)	(3576.9)	(20.970)	(1.416)	(26.440)
δ(S.D.)	-0.655*	-0.269*	0.258*	0.323*	0.140*
	(10.098)	(9.793)	(7.004)	(6.003)	(2.704)
α	0.392**	0.457*	0.327	0.156*	-0.115**
	(1.954)	(2.724)	(1.343)	(2.069)	(1.848)
β	-0.092	-0.200**	-0.374	-0.099	0.168
	(1.023)	(1.832)	(0.641)	(1.025)	(1.686)
γ	0.584*	0.373*	0.261	0.112	-0.621*
	(2.463)	(3.196)	(1.119)	(0.216)	(3.335)
ω	0.000	0.000*	0.0000	0.000	0.000
	(0.000)	(15.648)	(0.379)	(1.367)	(0.543)
ρ	1.000*	0.997*	0.973*	0.985*	0.965*
	(31.447)	(369.396)	(12.489)	(79.468)	(13.262)
φ	0.085	0.443*	0.329*	0.581*	0.484*
	(0.382)	(2.203)	(4.799)	(8.334)	(5.919)
LL	1052.57	807.9	977.89	1033.8	1026

All estimations used the Bollerslev-Wooldridge adjusted standard errors and covariances. See equations (1), (2) and (3) for details on parameters. LL is the log likelihood. The z-statistics are in parentheses, with * (**) indicating significance at the 5% (10%) level.

Table 5 CGARCH-M results for the Difference in Logged Case-Shiller House Price Indices (sub-samples)

City	Chicago (87m2-90m2)	Chicago (90m3-07m3)	LA (87m2-93m12)	LA (94m1-03m6)	LA (03m7-07m9)	Miami (87m2-00m10)	Miami (00m11 -04m1)	Miami (04m2-07m8)	Portland (87m02-91m03)	Portland (91m04-05m02)	NY (87m2-91m4)	NY (91m5-02m3)	NY (02m4-07m3)
μ	0.013	-0.003*	0.002*	0.009*	0.018*	-0.008*	0.014*	0.020*	-0.025*	0.010*	-0.110*	-0.004*	0.011
	(1.495)	(578.4)	(2.291)	(22.972)	(22.246)	(360.7)	(40.243)	(19.603)	(8084.8)	(35.821)	(5.263)	(8.414)	(44.268)
δ	-0.618	1.976*	-0.124	-0.402*	-0.351*	2.745*	-0.998*	-0.605*	4.460*	-1.230*	1.833*	2.607*	-0.284
SD	(0.622)	(15.370)	(1.034)	(4.536)	(2.572)	(7.843)	(5.943)	(3.035)	(25.176)	(9.278)	(4.342)	(14.409)	(3.843)
α	0.193	-0.062	-0.112	0.640*	0.560	0.089	0.438*	0.436	0.030	0.100**	-0.127*	0.012	0.006
	(0.149)	(0.147)	(0.906)	(6.375)	(0.146)	(0.287)	(2.089)	(0.325)	(0.212)	(1.859)	(2.177)	(0.184)	(0.214)
β	0.286	-0.179*	-0.102	-0.322*	-0.068	0.069	-0.026	0.212	0.182*	-0.119	-0.135	-0.043	-0.225
	(0.890)	(2.020)	(1.023)	(2.758)	(0.224)	(0.947)	(0.090)	(0.603)	(2.231)	(1.579)	(0.813)	(0.395)	(2.771)
γ	0.116	0.186	-0.379	0.253**	0.467	0.021	-0.279	0.139	0.056	-0.846	0.084	0.122	-0.364**
	(0.070)	(0.270)	(1.118)	(1.914)	(0.112)	(0.075)	(0.871)	(0.083)	(0.099)	(4.929)	(0.139)	(0.091)	(1.701)
ω	0.000*	0.000*	0.0000*	0.000	0.000	0.000*	0.000*	0.0000*	0.000	0.000*	0.000*	0.000*	0.0000
	(3.774)	(9.377)	(56.400)	(0.049)	(0.220)	(3.663)	(33.133)	(8.683)	(127)	(7.803)	(2.339)	(0.552)	(0.242)
ρ	0.037	0.387	0.660*	0.989*	0.976*	0.393	0.925*	0.648	0.585*	0.732*	1.038*	0.994*	0.984
	(0.030)	(0.869)	(4.739)	(41.509)	(6.341)	(0.251)	(6.959)	(0.294)	(2.998)	(2.182)	(13.587)	(79.090)	(13.974)
φ	0.085	0.216	0.968*	0.167	0.231	-0.015	-0.330*	0.112	0.115	0.055	0.156*	0.132*	0.869
	(0.382)	(0.521)	(6.009)	(1.316)	(0.057)	(0.052)	(2.876)	(0.090)	(0.729)	(1.461)	(2.250)	(5.450)	(10.646)
LL	122.46	876.4	269.8	456.8	173.0	677.8	188.1	146.3	184.2	697.9	207.7	593.3	256.5

All estimations used the Bollerslev-Wooldridge adjusted standard errors and covariances. See equations (1), (2) and (3) for details on parameters. LL is the log likelihood. The z-statistics are in parentheses, with * (**) indicating significance at the 5% (10%) level.

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Table 6 Tests for the equality of means and variances of each pair of contiguous segments

Segments (no of obs.)	F-test	Siegel-Tukey	Bartlett	Levene	Brown-Forsythe	t-test	Satterthwaite-Welch t-test†	Anova F-test	Welch F-test†
Ch 1 (37) & 2 (205)	7*	7.62*	83.26*	144.49*	125.18*	2.39*	1.33	5.7*	1.78
Ch 2 (205) & 3 (19)	2.82*	6.13*	11.67*	10.91*	8.31*	13.76*	9.03*	189.39*	81.54*
Ch 3 (19) & 4 (3)	2.55	2.3*	0.86	1.44	0.21	6.54*	4.6*	42.73*	21.12*
La 1 (83) & 2 (114)	3.61*	6.51*	38.95*	60.19*	43.19*	-2.25*	-2.06*	5.06*	4.23*
La 2 (114) & 3 (51)	4.14*	5.99*	38.68*	54.74*	50.37*	-2.54*	-2**	6.43*	3.98**
La 3 (51) & 4 (16)	3.67*	4.11*	7.38*	11.07*	10.37*	10.95*	14.95*	119.81*	223.44*
Mi 1 (165) & 2 (39)	3.12*	6.38*	15.46*	4.38*	4.36*	-12.39*	-17.24*	153.49*	297.16*
Mi 2 (39) & 3 (43)	32.45*	6.55*	81.85*	64.71*	34.33*	0.5	0.52	0.25	0.27
Mi 3 (43) & 4 (17)	3.1*	3.38*	5.96*	8.1*	4.24*	10.89*	13.7*	118.7*	187.58*
Ny 1 (51) & 2 (131)	3.53*	5.92*	32.47*	18.99*	14.59*	-5.48*	-4.26*	30.02*	18.12*
Ny 2 (131) & 3 (61)	2.12*	5.42*	12.37*	9.82*	5.3*	-5.79*	-5.07*	33.48*	25.69*
Ny 3 (61) & 4 (12)	11.41*	4.35*	15.47*	10.67*	6.61*	9.08*	17.25*	82.37*	297.62*
Ny 4 (12) & 5 (9)	14.2*	3.38*	13.76*	23.32*	15.78*	0.7	0.62	0.49	0.38
Por 1 (50) & 2 (167)	3.64*	2.58*	37.64*	25.48*	22.21*	2.41*	1.76**	5.83*	3.08**
Por 2 (167) & 3 (34)	4.1*	4.44*	35.57*	55.2*	49.83*	-3.58*	-2.33*	12.82*	5.43*
Por 3 (34) & 4 (13)	1.79	3.06*	1.31	3.57**	3.02*	8.83*	10.05*	77.98*	101.09*

See Table 3 and text for details of tests.